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CAR-TR-112
CS-TR-1479

March 1985

EDGE INFORMATION IN COLOR IMAGES BASED ON HISTOGRAMS OF DIFFERENCES

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ABSTRACT

A new measure of edge information for color images based on cumulative histograms of absolute color differences is proposed. A multispectral version of the Symmetric Nearest Neighbor filter for edge-preserving smoothing and methods for image segmentation and edge detection are developed based on this measure. Experimental results show that the performance of the new algorithms is very good.

The support of the Defense Reserach Projects Agency and the U.S. Army Night Vision and Electro-Optics Laboratory under contract DAAK70-83-0018 (DARPA order 3206) is gratefully acknowledge. Matti Pietikainen also thanks the Academy of Finland for support.

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1. Introduction

The analysis of color images has received relatively little attention in computer vision research, in spite of the facts that color plays an important role in human vision and that color should also provide much useful information for many image analysis applications. Image preprocessing by smoothing, region-based segmentation and edge detection are among the basic and most important steps in most applications. A wide variety of methods for these tasks have been developed for gray scale images, but only a few for color images.

A general introduction to color image processing and analysis is given by Pratt [1]. The applications of human visual color models to computer vision are reviewed by Granrath [2] and Gershon [3]. A comparative study of color features was carried out by Ohta et al.[4]. Among the color segmentation approaches proposed in the literature are the histogram splitting method of Ohlander et al. [5] and its successors [6], clustering methods by Schachter et al. [7] and Sarabi and Aggarwal [8], and a method based on edge-preserving smoothing by Nagao et al. [9]. For color edge detection an extension of the Hueckel edge operator was proposed by Nevatia [10] and a mask technique by Robinson [11]. A color smoothing method using global distribution of pixel values was proposed by Kitchen et al. [12].

This paper presents a measure of edge information for color images, which can be used for smoothing, segmentation and edge detection. We investigate the color information in histograms of first-order color differences. A multispectral

version of the Symmetric Nearest Neighbor filter [13] for edge-preserving smoothing, and methods for region-based segmentation and edge detection are developed.

These methods are based on cumulative histograms of absolute color differences computed in a single pass through the image. Histograms of first-order gray scale differences have been used by, among others, Nagao et al. for threshold selection [9] and Gotoh et al. [14] for analyzing properties of median filters .

In this paper we give examples of our approach using two-band data. The methods, however, generalize straightforwardly to three-band color data.

2. Histograms of Color Differences

The global histogram of absolute color (or gray scale) differences provides a good measure of edge information in an image, because the likelihood that an absolute color difference occurs in the interior of a region decreases monotonically with increasing magnitude of the difference. The general form of the histogram of absolute gray level differences is depicted in Figure 1. The high peak on the left comes from differences inside homogeneous areas and the small peak on the right from edges between regions. In the multidimensional case the differences at edges are sparsely scattered and usually no significant peaks exist in the histogram. The peak caused by homogeneous areas is very high and it decreases sharply with increasing absolute gray scale or color difference.

A difference histogram is computed in one pass through the image by considering absolute differences between a given pixel and its four neighbors.

Instead of using the original histogram, we can easily compute a cumulative histogram of absolute color differences, in which we can be certain that the frequencies are monotonically related to the magnitudes of the differences. Here the cumulative frequency associated with a given absolute color difference is the frequency of all differences which are greater than or equal to it in each coordinate. This cumulative frequency corresponds to the area of the rectangle in the original 2-color histogram determined by the given value at its corner (Figure 2).

3. Edge-Preserving Smoothing

The Symmetric Nearest Neighbor (SNN) filter recently introduced by Harwood et al. [13] uses both spatial and nearest-neighbor constraints on image pixels to smooth an image. To compute the gray value for the center pixel in a local neighborhood, it selects half the number of pixels in the neighborhood by selecting, from each pair of pixels located symmetrically on opposite sides of the center pixel, the one closer in gray value to the center pixel. In case of tied pairs, the mean of the pair is used. Then the mean value of those selected is substituted for the original value.

To find symmetric nearest neighbors for a multiband image, the following procedure is proposed:

1. Compute the multidimensional cumulative histogram of absolute color differences.

2. For each symmetric pair of neighbors in a local neighborhood, compute the absolute color differences between the two pixels in the pair and the center pixel. The pixel with a higher frequency in the cumulative histogram (smaller color difference) is selected. In case of ties, the mean of the symmetric pair is used. The mean of the values of the set of pixels selected is assigned to the center pixel on each band.

The color-SNN filter can be iterated and it converges without producing artifacts; normally only very small changes occur in the image after 2-3 iterations. The hardware implementation of the color-SNN using a 3 by 3 neighborhood should be almost as straightforward as in case of the basic SNN filter [15].

The histogram of differences can also be used for other nearest-neighbor operations. A color version of the k-nearest neighbor filter [16] can be implemented by selecting the k neighbors with the smallest color difference (highest values in the cumulative histogram) for averaging.

4. Segmentation

Our method of color segmentation combines edge-preserving smoothing with a simple connected components (CC) algorithm, in which adjacent pixels are said to be connected if the likelihood or frequency of the color difference is large (so the magnitude of the difference is small). The algorithms make use of the com-

bined information in the two-band image. A gray-scale version of the CC algorithm is described in [17]; both versions are modifications of the usual one for binary images [18].

This approach is similar to that of Nagao et al. [9], except that they used a different edge-preserving filter [19] to smooth each band separately. Then small level regions of the separate bands were merged depending on multiple thresholds, one for each band, to determine the connectivity of 4-adjacent neighbors. This method performs fairly well, although it has some weaknesses. The smoothing filter tends to distort edges and to create artifacts; also, because the bands are separately smoothed, there are often inconsistencies between bands, which are especially noticeable at region boundaries. In addition, there is the problem of selecting proper thresholds for the separate bands.

Now we will describe the present approach to color segmentation which minimizes the weaknesses of Nagao's method.

First the image is smoothed by the color-SNN filter. Normally, 2-3 iterations of 3 by 3 filtering are needed to sharpen edges and smooth homogeneous areas. To make edges even sharper and to avoid mismerging of regions at some critical points, bands are edge-enhanced with a gray-scale filter (MINRANGE) using a modification of the "least variation" principle of Nagao and Matsuyama's smoothing algorithm [19]. The MINRANGE filter replaces the center value of a 3 by 3 neighborhood by the mean of the 4-pixel "corner" subgroup (of the eight such, including the center) having the smallest range. Because sharpening is applied to almost completely smoothed bands, no artifacts are generated. More

discussion on sharpening and on recent studies with single-band SNN smoothing is presented in [20].

After the color image is smoothed, it is segmented by a two-pass connected components (CC) algorithm, in which adjacent pixels are said to be connected if the likelihood or frequency of their absolute color differences is sufficiently large. The only parameter is a threshold, expressed as a centile of frequencies, which is supplied by the user.

First, the two-band histogram of absolute color difference is computed, which is first converted to a two-band histogram of cumulative frequencies and finally to centiles of their distribution.

The two passes of the CC algorithm are the same as those of the standard one. Row by row, pixels are assigned labels by comparing each pixel with the four adjacent pixels above or to the left, which have already been labeled as the image is scanned from top to bottom, left to right. Then, in the second pass, the pixels with component-equivalent labels are relabeled uniquely.

5. Edge Detection

In this section we describe a method for detecting color edges using the difference histogram approach.

The magnitude of a color edge at a pixel might ordinarily be defined as the root-mean-square of the normalized band differences [21].

Here, after possibly smoothing the image with the color-SNN and MIN-RANGE filters, the cumulative histogram of absolute color differences is computed and converted to centiles of the distribution of cumulative frequencies. Then the color edge-value at a pixel is the maximum centile of the cumulative frequencies of the color differences between the center pixel and its eight neighbors. By thresholding, we obtain a binary edge image.

6. Experiments and Discussion

Figure 3 shows the red and green bands of a color image of a house. The size of the image is 255 by 192 pixels with eight bits per pixel. Figure 4 shows the same bands after two iterations and Figure 5 after five iterations of color-SNN smoothing. The images become much smoother (note the tree) and the edges are well preserved. The difference between Figures 4 and 5 seems to be small.

A good way to evaluate the effectiveness of smoothing is to consider its effects on segmentation. Because our CC segmentation is very sensitive, depending on single linkage of adjacent pixels, the results will be poor if the image is not well smoothed while enhancing edges at important region boundaries. In the following figures, the borders are black while the interiors are constant at the mean of the maximum and minimum values of the bands.

Figure 6 shows the segmentation of the original, unsmoothed image using a centile threshold of 75, and the result is as poor as expected.

After two iterations of color-SNN smoothing the segmentation is much better. Figure 7a shows the result for the threshold 75, and Figure 7b for the threshold 80. A further slight improvement is obtained by five iterations, with the result at the threshold 80 shown in Figure 8.

Even more details can be segmented if the edges are enhanced by a postprocessor after color-SNN smoothing. In our examples we used the MINRANGE filter described in Section 4. Figure 9a shows the segmentation after two iterations of color-SNN smoothing and two iterations of sharpening with MINRANGE, and Figure 9b the segmentation after five iterations of color-SNN smoothing and three iterations of sharpening. The threshold value is 80.

In order to further study the effects of iterations and sharpening we did experiments with a higher threshold, 85, which should cause unwanted merging. In this case, two or five iterations of color-SNN smoothing without sharpening did not give very good results (Figures 10a and 10b). The results for two iterations of color-SNN with two iterations of sharpening (Figure 10c) and for five iterations of color-SNN with three iterations of sharpening (Figure 10d) are very good. These and other experiments we performed suggest that 2-3 iterations of color-SNN followed by 2-3 iterations of sharpening is easily sufficient for good results; very few changes in segmentation occur with more iterations.

In another example we used the red and blue bands of an image of a room (Figure 11). The size of the images is 256 by 256 pixels with eight bits per pixel. The segmentation of the original bands is shown in Figure 12a, the results after two iterations of color-SNN in Figure 12b, and after two iterations of color-SNN

followed by one iteration of sharpening in Fi ure 12c. The threshold value is 85. The segmentation of the original image is poor, while the other segmentations are very good.

Figure 13a shows the color edges computed for the original, unsmoothed two-band color image. Figure 13b shows the edges after two iterations of color-SNN, and Figure 13c after two iterations of color-SNN followed by two of MIN-RANGE sharpening. It can be seen that the color-SNN alone gives good results, and that the effect of the sharpening is not important for this image.

The methods were also tested on a set of road images digitized from a video-tape. Figures 14a and 14b show the green and blue bands of a road image, which has a highly textured background and a shadow on the road. The segmentation of the shadow is a very difficult task. The size of the image is 128 by 128 pixels with eight bits per pixel. Figures 14c and 14d show the same bands after three iterations of color-SNN smoothing. The textured areas have become significantly smoother.

Figure 15a shows the segmentation (threshold 80) after three iterations of color-SNN followed by two iterations of sharpening and Figure 15b shows the segmentation without sharpening. Figure 15c shows the color edges for the case of Figure 15a, and Figure 15d for the case of Figure 15b, with a threshold of 95.

In our previous examples we used images having eight bits per pixel. The size of the difference histogram is 256 by 256 bins for 8-bit data. We also did comparative experiments with 6-bit data, in which case the histogram has 64 by

64 bins. The results were almost identical, even though in the latter case nearly 80 percent of the absolute differences were in the nine bins nearest to the origin for a smoothed image. This suggests that a three-band version of our approach could be easily implemented by using 6-bit data or by using adaptively quantized histograms.

7. Conclusions

A new measure of edge information for color images based on cumulative histograms of absolute color differences was introduced. Methods based on this measure were developed for edge-preserving smoothing, segmentation, and edge detection. The methods performed well in experiments. Among the good features of the methods are that they are relatively simple, they do not possess many parameters, and they seem to give good results for many different types of images even when using the same set of parameter values for these different images.

Acknowledgements

We wish to thank Mark Westling, who wrote a gray scale version of the connected components algorithm used in this study. We also thank Dr. Larry S. Davis for his comments.

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FIGURE CAPTIONS

Figure 1. Histogram of absolute gray level differences.

Figure 2. Determination of cumulative 2-color frequencies.

Figure 3. Original bands of house image.

a) Red

b) Green

Figure 4. Bands after two iterations of color-SNN smoothing.

a) Red

b) Green

Figure 5. Bands after five iterations of color-SNN smoothing.

a) Red

b) Green

Figure 6. Segmentation of original bands (threshold 75).

Figure 7. Segmentation after two iterations of color-SNN:
a) threshold 75 b) threshold 80

Figure 8. Segmentation after five iterations of color-SNN (threshold 80)

Figure 9. Segmentation after two iterations of color-SNN and two iterations of sharpening (a), and after five iterations of color-SNN and three iterations of sharpening (b); threshold 80.

Figure 10. Segmentation with threshold 85:

a) two iterations of color-SNN
b) five iterations of color-SNN
c) two iterations of color-SNN and two iterations of sharpening
d) five iterations of color-SNN and three iterations of sharpening

Figure 11. Red and blue bands of room image.

a) Red

b) Blue

Figure 12. Segmentation with threshold 85:

a) for original bands
b) after two iterations of color-SNN
c) after two iterations of color-SNN
and one iteration of sharpening

Figure 13. Color edges of house image, with threshold 90:

a) for original bands
b) after two iterations of color-SNN
c) after two iterations of color-SNN
and two iterations of sharpening

Figure 14. A road image.

a) green
b) blue
c) green after three iterations of color-SNN
d) blue after three iterations of color-SNN

Figure 15.

a) Segmentation with threshold 80 after three iterations
of color-SNN and two iterations of sharpening
b) Segmentation without sharpening
c) Edges for (a) with threshold 95
d) Edges for (b) with threshold 95

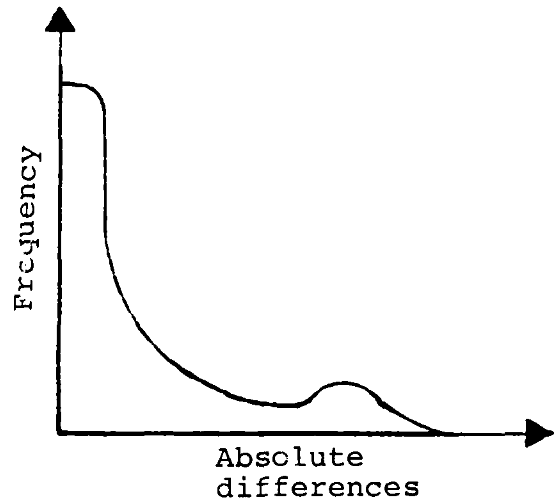


Figure 1. -- Histogram of absolute gray level differences.

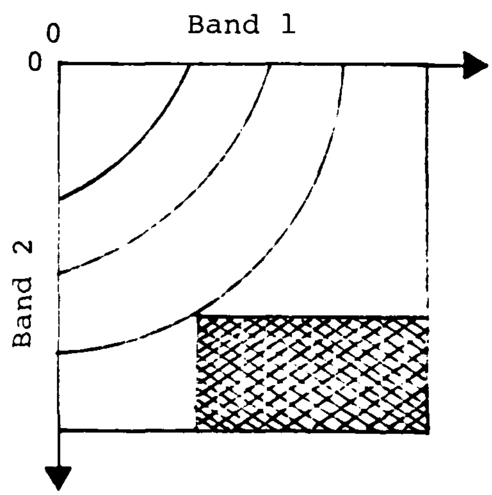
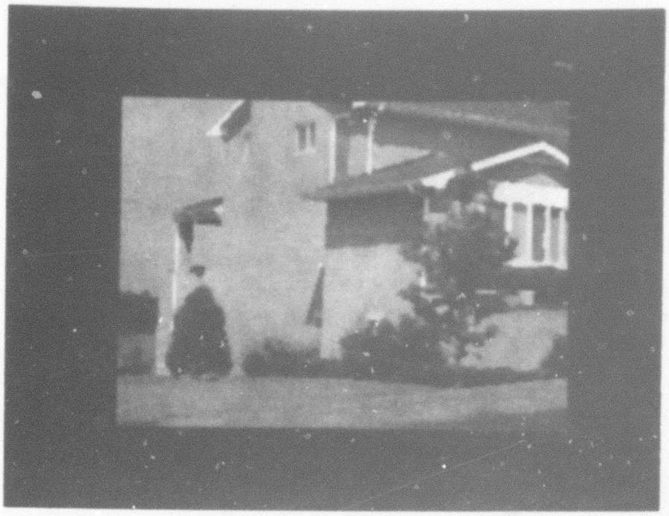


Figure 2. -- Determination of cumulative 2-color frequencies.

a) Red

b) Green

Figure 3. -- Original bands of house image.



a) Red

b) Green

Figure 5. -- Bands after 5 iterations of color-SNN smoothing.

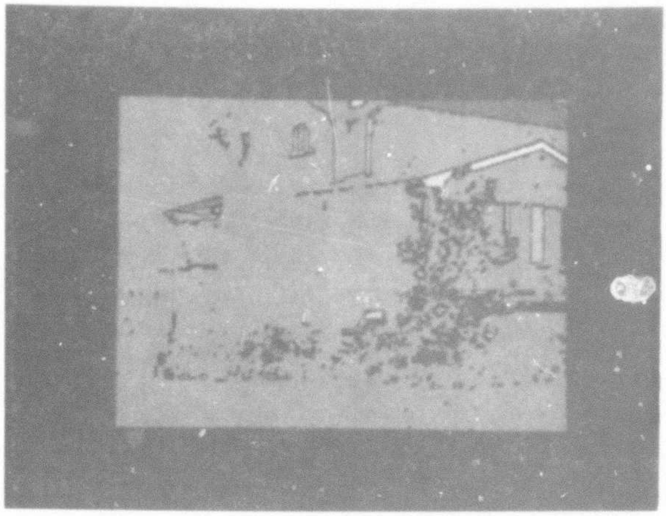


Figure 6. -- Segmentation of original bands (threshold 75).

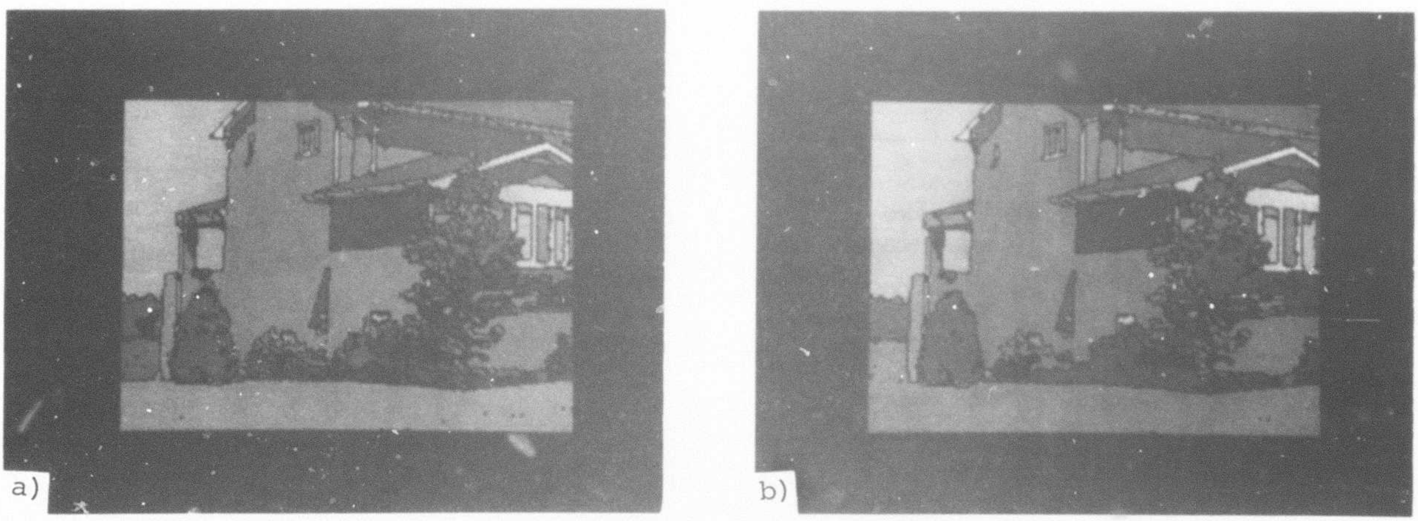


Figure 7. -- Segmentation after 2 iterations of color-SNN.
a) threshold 75   b) threshold 80

Figure 8. -- Segmentation after 5 iterations of color-SNN (threshold 80)

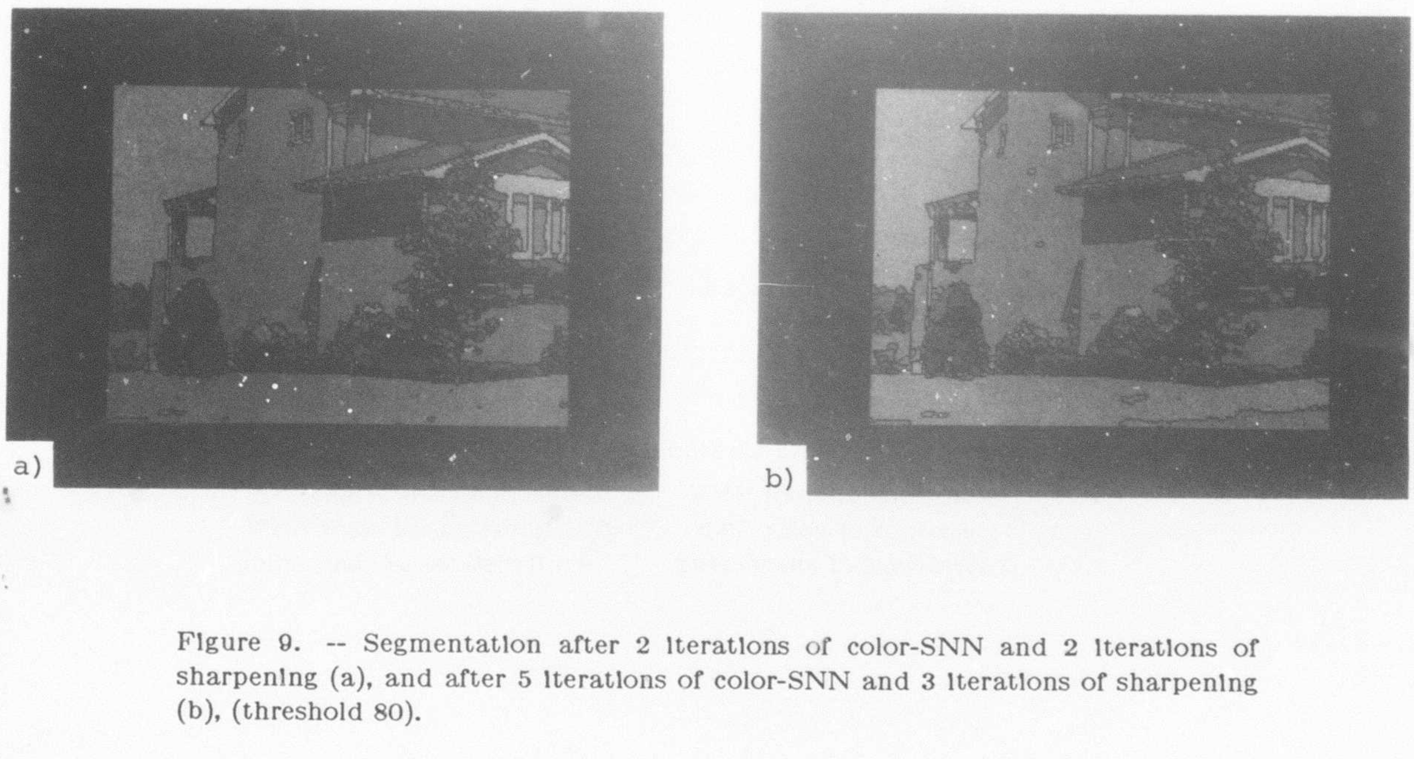


Figure 9. -- Segmentation after 2 iterations of color-SNN and 2 iterations of sharpening (a), and after 5 iterations of color-SNN and 3 iterations of sharpening (b), (threshold 80).

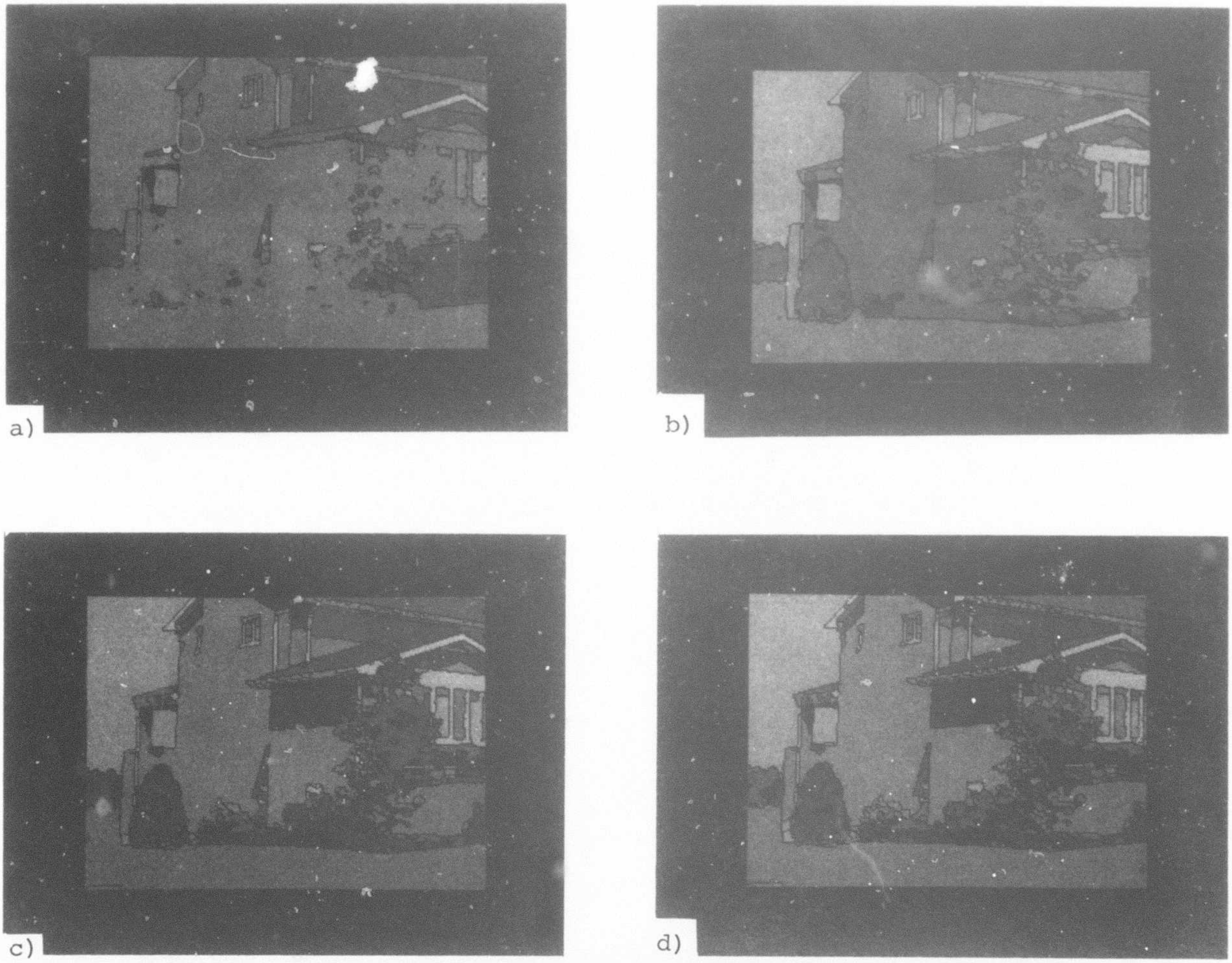
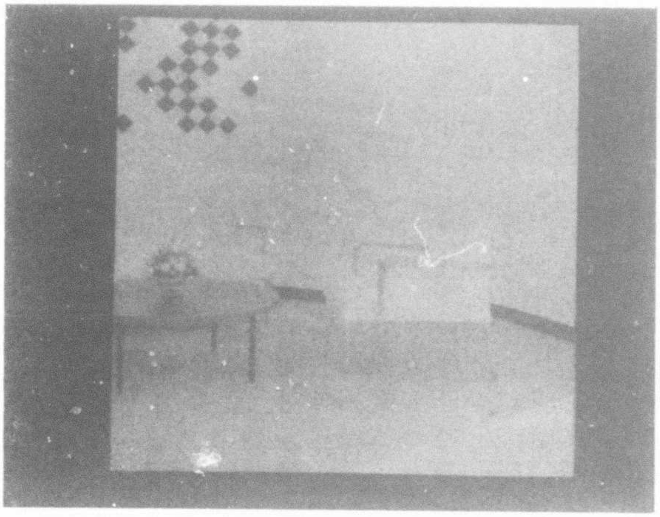
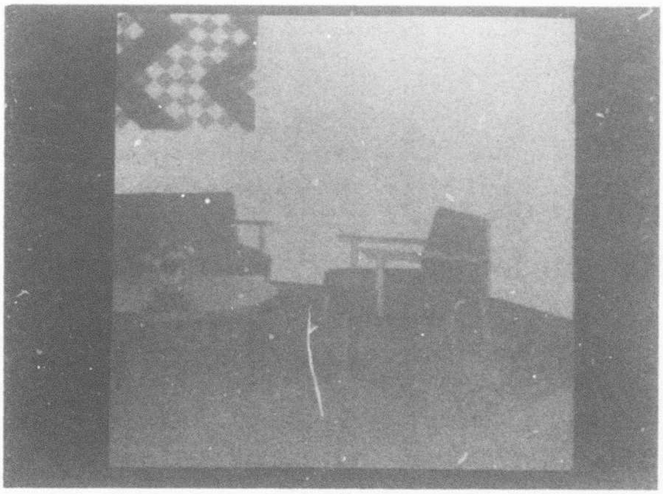


Figure 10. -- Segmentation with threshold 85.

a) 2 iterations of color-SNN
b) 5 iterations of color-SNN
c) 2 iterations of color-SNN + 2 iterations of sharpening
d) 5 iterations of color-SNN +3 iterations of sharpening

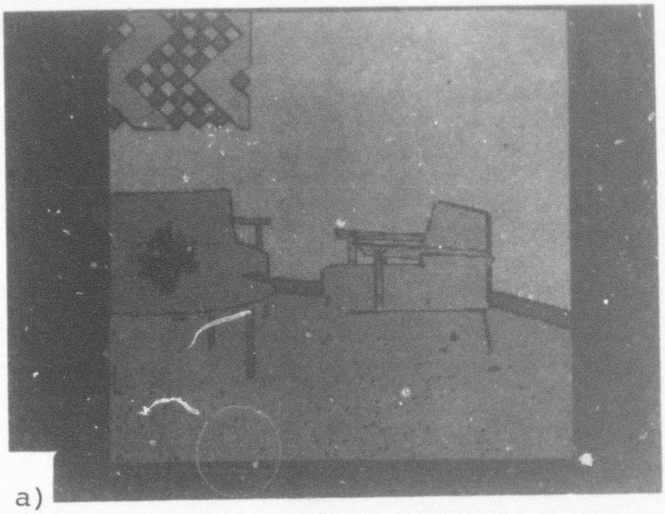


a) Red

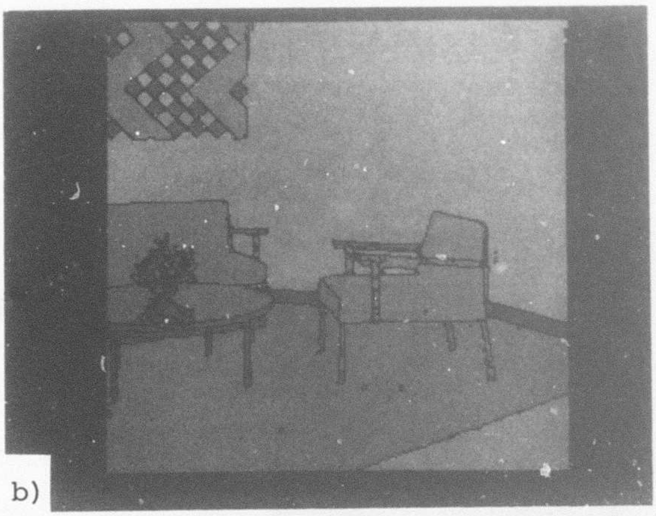


b) Blue

Figure 11. -- Red and blue bands of room image.



a)



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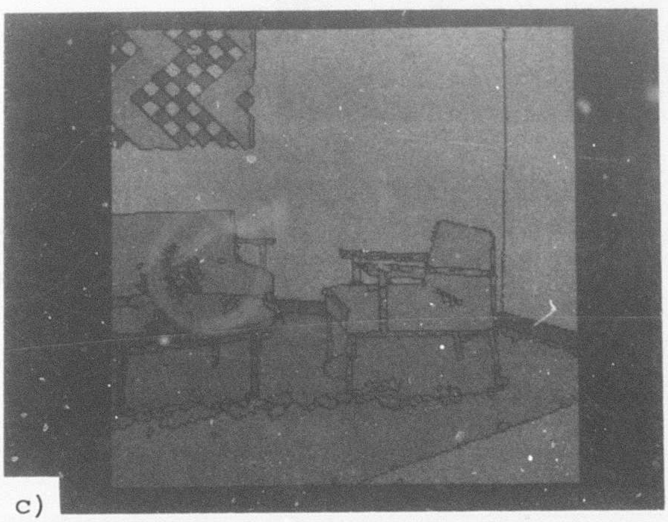

c)

Figure 12. -- Segmentation with threshold 85.

a) for original bands
b) after 2 iterations of color-SNN
c) after 2 iterations of color-SNN
and 1 iteration of sharpening

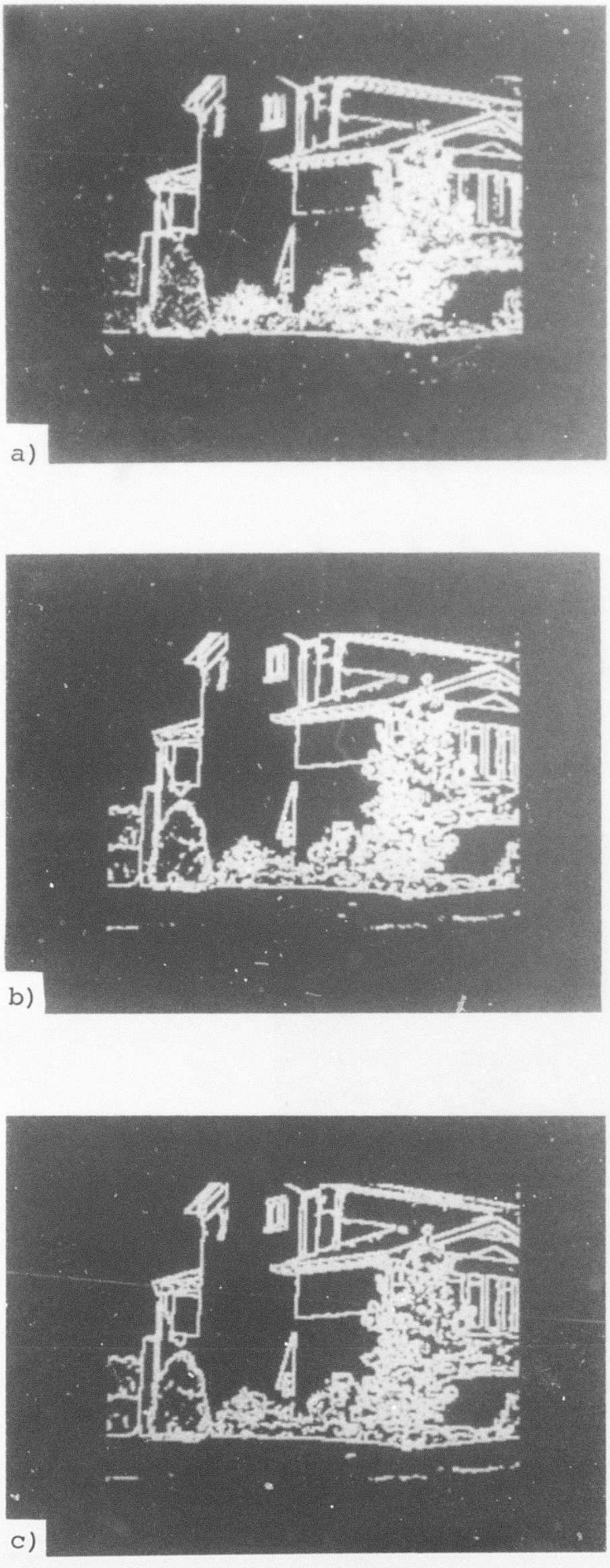

Figure 13. -- Color edges of house image, with threshold 90.

a) for original bands
b) after 2 iterations of color-SNN
c) after 2 iterations of color-SNN and 2 iterations of sharpening

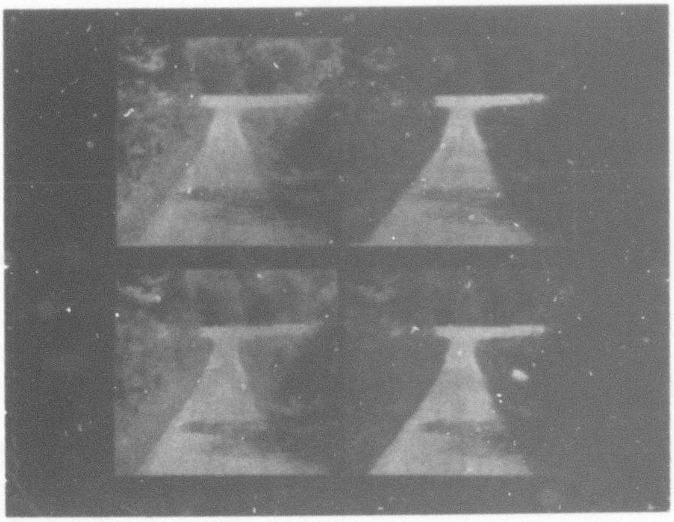

Figure 14. -- A road image.

a) green
b) blue
c) green after 3 iterations of color-SNN
d) blue after 3 iterations of color-SNN

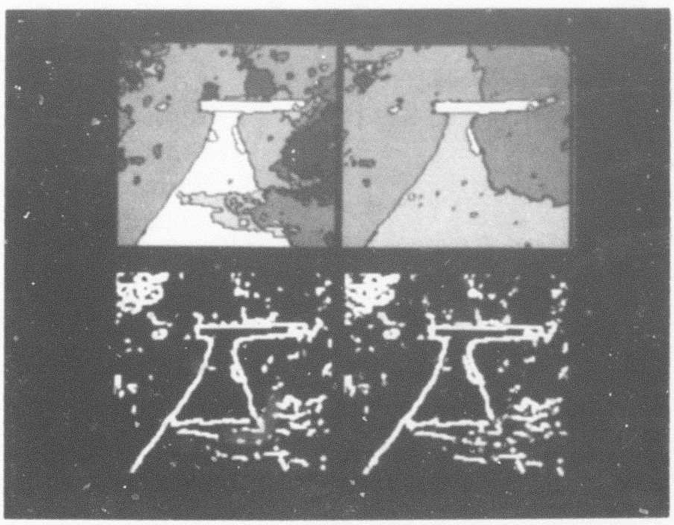

Figure 15.

a) Segmentation with threshold 80 after 3 iterations of color-SNN + 2 iterations of sharpening
b) Segmentation without sharpening
c) Edges for (a) with threshold 95
d) Edges for (b) with threshold 95

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION
UNCLASSIFIED

1b. RESTRICTIVE MARKINGS
N/A

2a. SECURITY CLASSIFICATION AUTHORITY
N/A

2b. DECLASSIFICATION/DOWNGRADING SCHEDULE
N/A

3. DISTRIBUTION/AVAILABILITY OF REPORT
Approved for public release;
distribution unlimited

4. PERFORMING ORGANIZATION REPORT NUMBER(S)
CAR-TR-112
CS-TR-1479

5. MONITORING ORGANIZATION REPORT NUMBER(S)
N/A

6a. NAME OF PERFORMING ORGANIZATION
University of Maryland

6b. OFFICE SYMBOL *(If applicable)*
N/A

7a. NAME OF MONITORING ORGANIZATION
U.S. Army Night Vision and Electro-Optics Laboratory

6c. ADDRESS (City, State and ZIP Code)
Center for Automation Research
College Park, MD 20742

7b. ADDRESS (City, State and ZIP Code)
Fort Belvoir, VA 22060

8a. NAME OF FUNDING/SPONSORING ORGANIZATION
DARPA

8b. OFFICE SYMBOL *(If applicable)*
IPTO

9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER
DAAK70-83-K-0018

8c. ADDRESS (City, State and ZIP Code)
1400 Wilson Blvd.
Arlington, VA 22209

10. SOURCE OF FUNDING NOS.

PROGRAM ELEMENT NO.	PROJECT NO.	TASK NO.	WORK UNIT NO.

11. TITLE (Include Security Classification)
EDGE INFORMATION IN COLOR IMAGES BASED ON HISTOGRAMS OF DIFFERENCES

12. PERSONAL AUTHOR(S)
Matti Pietikäinen and David Harwood

13a. TYPE OF REPORT
Technical

13b. TIME COVERED
FROM ______ TO ______ N/A

14. DATE OF REPORT (Yr., Mo., Day)

15. PAGE COUNT
26

16. SUPPLEMENTARY NOTATION

17. COSATI CODES

FIELD	GROUP	SUB. GR.

18. SUBJECT TERMS *(Continue on reverse if necessary and identify by block number)*

19. ABSTRACT *(Continue on reverse if necessary and identify by block number)*

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20. DISTRIBUTION/AVAILABILITY OF ABSTRACT
UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT. ☐ DTIC USERS ☐

21. ABSTRACT SECURITY CLASSIFICATION
UNCLASSIFIED

22a. NAME OF RESPONSIBLE INDIVIDUAL

22b. TELEPHONE NUMBER *(Include Area Code)*

22c. OFFICE SYMBOL